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0/1 point

1.	Which of the	following are true?	(Check all that apply.)	

 ${f W}_1$ is a matrix with rows equal to the parameter vectors of the first layer.

! This should not be selected

No. The notation convention is that the superscript number in brackets indicates the number of layers.

 $\stackrel{[4]}{\smile} w_3^{[4]}$ is the row vector of parameters of the fourth layer and third neuron.

This should not be selected

No. The vectors $\boldsymbol{w}_k^{[j]}$ are column vectors.

 $oxed{ \begin{tabular}{c} W^{[1]} \end{tabular}}$ is a matrix with rows equal to the transpose of the parameter vectors of the first layer.

 $\ensuremath{ullet} W^{[1]}$ is a matrix with rows equal to the parameter vectors of the first layer.

! This should not be selected

No. The parameter vectors are column vectors.

 $w_3^{[4]}$ is the column vector of parameters of the fourth layer and third neuron.

✓ Correct

Yes. The vector $\boldsymbol{w}_j^{[i]}$ is the column vector of parameters of the i-th layer and j-th neuron of that layer.

 $u_3^{[4]}$ is the column vector of parameters of the third layer and fourth neuron.

∠⁷ Expand

igotimes Incorrect

You didn't select all the correct answers

2. The sigmoid function is only mentioned as an activation function for historical reasons. The tanh is always preferred without exceptions in all the layers of a Neural Network. True/False?

1/1 point

False

○ True

∠⁷ Expand

⊘ Correct

Yes. Although the tanh almost always works better than the sigmoid function when used in hidden layers, thus is always proffered as activation function, the exception is for the output layer in classification problems.

3. Which of these is a correct vectorized implementation of forward propagation for layer l , where $1 \leq l \leq L$?

1/1 point

$$egin{aligned} iggl(Z^{[l]} &= W^{[l]}A^{[l]} + b^{[l]} \ A^{[l+1]} &= g^{[l]}(Z^{[l]}) \end{aligned}$$

$$\bigcirc \ \, Z^{[l]} = W^{[l-1]} A^{[l]} + b^{[l-1]} \\ A^{[l]} = g^{[l]} (Z^{[l]})$$

$$A^{[l]} = g^{[l]}(Z^{[l]})$$

∠ Expand

⊘ Correct

ReLU	
· · · · · ·	
sigmoid	
○ Leaky ReLU	
tanh	
∠ ⁷ Expand	
₹ Zypania	
⊙ Correct	
Yes. Sigmoid outputs a value between 0 and 1 which makes it a very good choice for binary classification. You can classify as 0 if the output is less than 0.5 and classify as 1 if the output is more than 0.5. It can be	
done with tanh as well but it is less convenient as the output is between -1 and 1.	
Consider the following code:	1/1 point
#+begin_src python	1/ 1 point
x = np.random.rand(4, 5)	
y = np.sum(x, axis=1)	
#+end_src	
What will be y.shape?	
(4, 1)	
(1, 5)	
(a,)	
(5,)	
vector with 4 entries. Since the option keepdims was not used the array doesn't keep the second dimension.	
Suppose you have built a neural network. You decide to initialize the weights and biases to be zero. Which of the following statements is true?	
	1/1 point
	1/1 point
Each neuron in the first hidden layer will perform the same computation in the first iteration. But after one iteration of gradient descent they will learn to compute different things	1/1 point
But after one iteration of gradient descent they will learn to compute different things because we have "broken symmetry".	1/1 point
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1/1 point

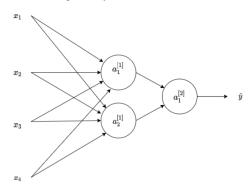
- They are the go to option when you don't know what activation function to choose for hidden layers.
- They are increasingly being replaced by the tanh in most cases.
- They cause several problems in practice because they have no derivative at 0. That is why Leaky ReLU was invented.
- They are only used in the case of regression problems, such as predicting house prices.



⊘ Correct

9. Consider the following 1 hidden layer neural network:

1/1 point



Which of the following statements are True? (Check all that apply).

- $igwedge W^{[1]}$ will have shape (2, 4).

✓ Correc

Yes. The number of rows in $W^{[k]}$ is the number of neurons in the k-th layer and the number of columns is the number of inputs of the layer.

w w

will have shape (4, 2).

\$\$b^{[1]}\$\$ will have shape (2, 1).

✓ Correct

Yes. $\$5^{[k]}$ is a column vector and has the same number of rows as neurons in the k-th layer.

\$\$W^{[2]}\$\$ will have shape (1, 2)

✓ Correct

Yes. The number of rows in $\$W^{([k])}\$$ is the number of neurons in the k-th layer and the number of columns is the number of inputs of the layer.

\$\$h^{[1]\\$\$ will have shane (4 2)

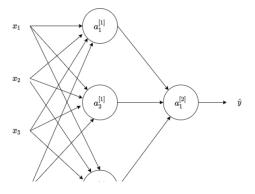
Expand

⊘ Correct

Great, you got all the right answers.

10. Consider the following 1 hidden layer neural network:

0/1 point



<i>x</i> .	V	 a ^[1]	V
204		u_3	

What are the dimensions of ${\cal Z}^{[1]}$ and ${\cal A}^{[1]}$?

- $\bigcirc \hspace{0.1in} Z^{[1]}$ and $A^{[1]}$ are (4, 1)
- $\bigcirc \quad Z^{[1]} \text{ and } A^{[1]} \text{ are (3, m)}$
- $igotimes Z^{[1]}$ and $A^{[1]}$ are (3, 1)
- $\bigcirc \quad _{Z^{[1]}}$

∠ Expand

 $\bigotimes \textbf{Incorrect} \\ \textbf{No. The } Z^{[1]} \textbf{ and } A^{[1]} \textbf{ are calculated over a batch of training examples. The number of columns in } Z^{[1]} \\ \textbf{ and } A^{[1]} \textbf{ is equal to the number of examples in the batch, m. And the number of rows in } Z^{[1]} \textbf{ and } A^{[1]} \textbf{ is equal to the number of neurons in the first layer.}$